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A Model for Stock Market Value Forecasting using Ensemble Artificial Neural Network

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ABSTRACT

Artificial Neural Network (ANN) is a model used in capturing linear and non-linear relationship of input and output data. Its usage has been predominant in the prediction and forecasting market time series. However, there has been low bias and high variance issues associated with ANN models such as the simple multi-layer perceptron model. This usually happens when training large dataset. The objective of this work was to develop an efficient forecasting model using Ensemble ANN to unravel the market mysteries for accurate decision on investment. This paper employed the Ensemble ANN modeling technique to tackle the high variations in stock market training dataset faced when using a simple multi-layer perceptron model by using the theory of ensemble averaging. The Ensemble ANN model was developed and implemented using NeurophStudio and Java programming language, then trained and tested using daily data of stock market prices from various banks, for a period of 497 days. The methodology adopted to achieve this task is the agile methodology. The output of the proposed predictive model was compared with four traditional neural network multilayer perceptron algorithms, and outperformed the traditional neural network multilayer perceptron algorithms. The proposed model gave an average to best predictive error for any day when compared with the other four traditional models.

1. Introduction

Stock can be described as a claim or share in ownership of a company. An organization or individual can claim company's assets and earnings if they purchase the company's stock. As an entity acquires more stock from an organization, their stake in the organization becomes greater. Stocks are sold and bought in a central place called the stock exchange market. "There is no doubt that the majority of the people related to stock markets is trying to achieve profit. Profit comes by investing in stocks that have a good future (short- or long-term future). Thus, what they are trying to accomplish one way or the other is to predict the future of the market for a profit-making venture into the stock market." [1]. Stock market can be likened to a random walk process [2] and predicting the stock market index is still considered as one challenging and difficult task for researchers, this is due to the uncertainties various influences involved in pushing the market have. These uncertainties, which are responsible for the high volatility of the stock market prices can be due to factors such as [3]:

(a) Movement of other stock markets: Due to the connection through stock different stock exchange markets have.
(b) Political Influence: Policies relating to stock market in the nation where the stock exchange market is located.
(c) Macro-economic factors: GDP, Inflation and Deflation rate, Profit and loss chart of the organizations.
(d) Individual Psychology: Human intuition coming to play while buying and selling stock, which in turn can affect the uncertainty of the market price.

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Forecasting in the financial time series is basically predicting the behavior of one step ahead of the series with the help of various variables. In finance practice, stock price prediction/forecasting have two conventional approaches namely fundamental analysis and technical analysis [4]. Techniques from both categories are also used by forecasters simultaneously for improving forecasting ability [5].

In the Artificial Intelligence community, forecasting the stock market is one of the biggest challenges. Different methods, such as Random Walk, Naïve Bayes, Aggressive Moving Average, Linear Regression, have been proposed but have come out with varying results. The aim of forecasting research has been largely beyond the analytic processes of traditional Artificial Intelligence research which has mainly focused on developing intelligent system that are supposed to emulate human intelligence [6].

Artificial neural networks are one of the relatively newly developed methods that have been widely used for forecasting purposes in different fields such as forecasting financial time series [7, 8]. Artificial neural networks have the ability to learn patterns [9] and can also self-organize during the learning process. The feedforward network, based on multilayer perceptron architecture, a network that learns by using the backpropagation algorithm to update network weights, is the most common form of artificial neural network (ANN) used for regression-type prediction [10]. Multilayer perceptron is in the family of feedforward artificial neural network algorithm that consists of three layers of nodes: an input layer, a hidden layer and an output layer [10, 11]; each node is a neuron that uses a nonlinear activation function. The activation function accepts neuron for each node from the input nodes used for the network training [10]. It can be distinguished from a single layer perceptron using its multiple layers and its nonlinear activation function. Backpropagation can be seen as a standard method for training feedforward neural networks; it is simply backpropagating errors from the output layer towards the input layers during the training process [12]. It trains the network by updating the input weights of the neural network based on the error rate obtained in the previous iteration. It reduces error rate with each iteration [1] thereby making the model reliable by increasing its generalization. To be able to learn stock market's relative pattern, nonlinear trend and variations, we chose to apply multilayer perception (MLP) architecture using Back propagation algorithm. Since it can create internal representations and learn different features in each layer. "Each layer finds patterns in the layer below it and it has this ability to create internal representations that are independent of outside input that gives multi-layered networks their power" [13]. This study uses the concept of ensemble artificial neural network models to provide an accurate prediction model for stock market forecasting.

Ensemble learning is a technique in machine learning, which can be seen as the process employed in training multiple machines learning models, combining their outputs, thereby treating them as a committee of decision makers. The reason for this is; this committee of individual models should have an overall better accuracy, on the average at least, than any single committee member [14]. Ensemble learning creates a group of models that produces low bias and high variance, and then combines them to produce a new model, which comes with a low bias and a low variance; this would overcome the limitation of high variance in the conventional Multilayer Perceptron backpropagation algorithm, which can be frustrating when preparing a final model for making predictions. Due to the stock market volatility [15], it requires efficient mechanism to unravel the market mysteries for accurate decision on investment.

Neural Networks are usually nonlinear in nature. They are highly flexible and can be scaled in proportion according to the amount of training data available. Their stochastic learning algorithm [16] can be a let-down of this flexibility, this means that they are sensitive to the specific training data used and each time they are trained by different instance of the dataset, they may find different set of weights, which in turn would produce different predictive errors.

Ensemble technique has been employed by many machine learning quiz winners, an example is using an ensemble technique to win the Special Interest Group on Knowledge Discovery and Data Mining 2009 cup challenge, which was to predict using data provided by Orange Telecom Company, the propensity of customers to switch service providers, buy new products or buy upgrades [17]. A good model or algorithm would definitely have predictions better than random chance, due to its skill. Importantly, the models must be good in different ways; a model can perform well for a particular instance of a dataset in relation to other listed models but also performs the least for a different batch.

2. Related Work

A methodical outline of the review done on carefully chosen literature on stock market forecasting is shown in Table 1.

Table 1 Summary of some related works.

Author	Purpose	Techniques	Findings
Mahdi et al [6]	Stock Market value prediction using neural networks.	Feedforward MLP and an Elman recurrent network to predict a company's stock value based on its stock share value history.	Their experimental results show that the application of MLP neural network is more promising in predicting stock value changes rather than Elman recurrent network and linear regression method.
Seyed and Saeid [7]	A journal on forecasting S&P 500 index using artificial neural networks and design of experiments.	Using ANN to discover and select the most influential factors of the proposed system that affects the daily direction of S&P 500.	It was discovered from the results that ANN model that uses the most influential features is able to forecast the daily direction of S&P 500 significantly better than the traditional logit model.
Devadoss and Ligori [19]	Forecasting of Stock Prices Using Multilayer Perceptron.	Using two Feedforward MLP network to predict Bombay Stock Exchange prices of selected sectors.	Neural Network based forecasting of stock prices of selected sectors under Bombay Stock Exchange show that neural networks have the power to predict prices.
Selmi et al [18]	Artificial neural network model to estimate the volatility of the daily S&P500 market returns.	A hybrid model where they combined ANN model with ARCH-M model in prediction S&P500 future prices.	The results obtained revealed that the model performed best for the selected criteria.
Sarat et al [3]	An adaptive second order neural network with genetic algorithm-based training to forecast the closing prices of the stock market.	Adaptive single layer second order neural network with genetic algorithm-based training (ASONN-GA).	Result shows that ASSONN-GA performed better than traditional neural networks.
Ozgur and Taha [5]	A literature review of stock market prediction performance of neural networks.	ANN combined with multivariate statistical models.	They found that a preliminary analysis using multivariate statistical techniques on datasets that would be fed to ANN promise a more profitable set of hybrid models.
Surbhi and Baijnath [4]	Quantitative analysis of stock market prediction for accurate investment decision in future.	Single decision tree, Discriminant analysis, Naive Bayes, Random Forest, Logistic Regression.	They discussed recent machine learning techniques along with pros and cons of each technique for effectively predicting the future stock price followed by various researchers.
Hoselnzade and Haratizadeh [8]	CNN-based stock market prediction using several sources.	Convolutional neural network.	The evaluations show a significant improvement in predictions performance compared to state-of-the-art baseline algorithms.

3. Methodology

In this study, Java programming language using Netbeans platform and simulations from Neuroph Studio were used to implement the model (Fig. 1). Java is a powerful programming language and NetBeans was the integrated development environment chosen for coding the java codes of the model. Neuroph Studio is a framework used for simulating artificial neural networks.

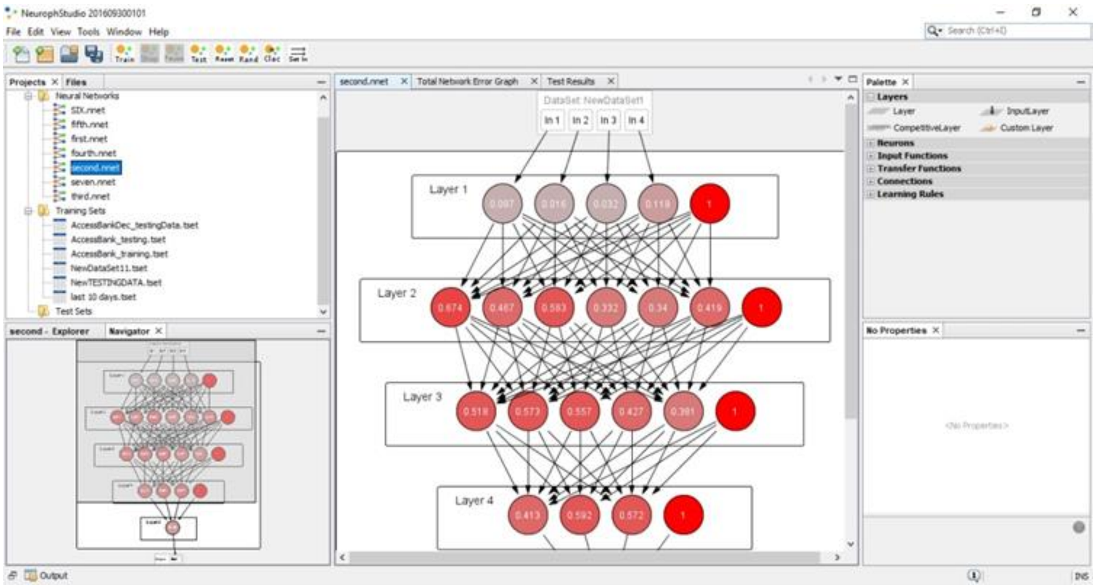

Fig. 1 Sample of One of the Trained Networks in NeurophStudio (Source: NeurophStudio 2.6).

3.1. Data Collection and Processing

Data were collected by using secondary method of data collection from the Banking Index of the Nigerian Stock Exchange, Lagos. Historical data were downloaded from the Nigerian section of 'investing.com', a credible stock market analysis website. The data collected is for a period of 496 days starting from January 2, 2019 to December 31, 2020 excluding weekends and public holidays. The normalization for the input was done using equation (1).

$$X_N = (X - X_{min}) / (X_{max} - X_{min}) \tag{1}$$

Where, X denotes the input value that should be normalized; X_N denotes the normalized value of X; X_{min} represents the minimum value of X; and X_{max} represents the maximum value of X.

After the normalization, the data (stock prices) were in the range of (0, 1). The data were grouped into batches/instances of 5 columns, divided into training and testing dataset and saved as comma separated value (.csv), then ready for analysis. Fig. 2 gives a graphical idea of data process throughout the model.

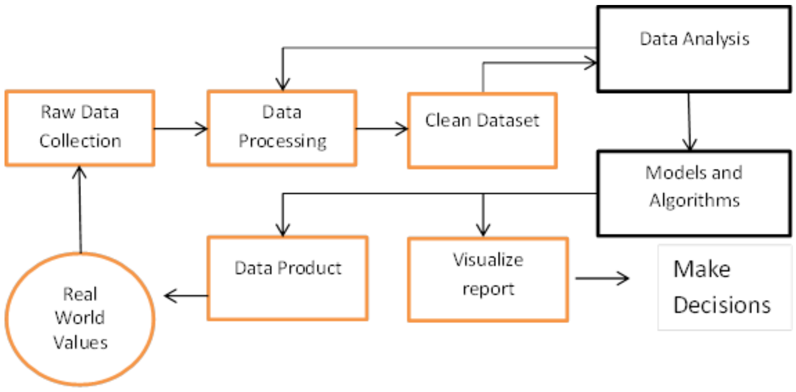

Fig. 2 Data Science Process.

3.2. Software Methodology Adopted

Agile methodology was adapted in this study to develop an ensemble model for stock market value prediction using artificial neural network. It was used because it divides the entire project in to smaller parts. This will help the researcher to work on each iteration leading to the system development life cycle. The steps include requirement analysis, design, Construction/Iteration (Development), coding and testing, Deployment and Feedback. The Agile methodology is shown in Fig. 3.

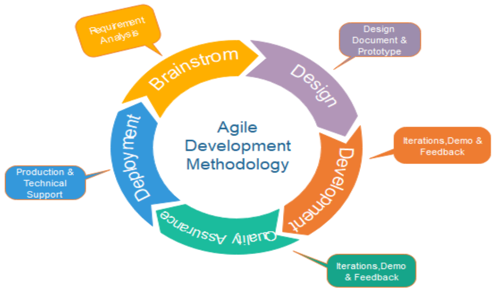

Fig. 3 Agile Methodology Life Cycle Model.

3.3. High Level Model Diagram of Ensemble Model

The high-level model diagram is shown in Fig. 4.

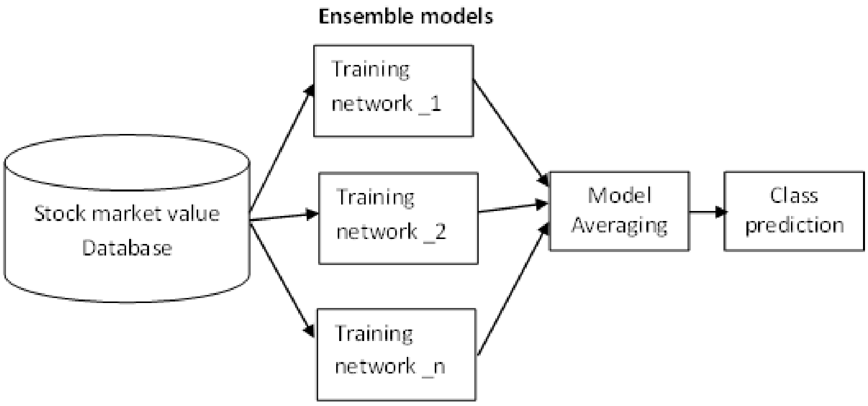

Fig. 4 High Level Model of the Proposed System.

Training the multiple neural networks requires initialization of input weights and the first weight adjusted until the optimal prediction of each of the single model is gotten. The average of training datasets of each of the network is computed to reduce high variance and produce efficient prediction model for the system.

The high-level diagram consists of "Stock market value Database," "ANN models", "model average" and "class prediction". The components are as follow:

(a) *Stock market value Database*: The stock exchange values are the historical data of the problem domain used for machine learning training and prediction.

(b) *Training Networks*: The forecasting models uses multilayer perceptron architecture based on Backpropagation Algorithm to train differently, stock market dataset, such that it positioned them to learn in different ways.

(c) *Model Averaging*: The mechanism of ensemble model uses model averaging as a varying combination technique to compute the varying degrees of each Neural Network model in the collections of the models. This gives the average prediction of the models.

(d) *Class Prediction*: The results of the averaged model of the training networks of the different neural network models are used to produce a single class prediction for the system. In ensemble model the class prediction is computed from samples with known training set, this establishes a prediction rule to predict new samples or test set.

3.4. Algorithm of Proposed System

The steps of the algorithms are as follows:

Step 1: Generate *N* machine learning model, each with its own initial weight parameters and same training data for input layers

Step 2: Train each of the neural network model separately

Step 3: Combine the neural network model and average their values

Step 4: Forecast stock market values

Step 5: Stop.

3.5. Ensemble Learning Model Technique

This technique is experimented on using four MLP networks, all with the same architecture but with different hyperparameters. Each of these networks learned using the feed forward algorithm to map the input and output function, and backpropagation algorithm to train the network and update the weights after each epoch. The following processes were used:

(a) Feed Forward Algorithm: Feed forward is a supervised learning algorithm and describes the "flow of information" through a neural network from its input layer to its output layer. The feed forward algorithm is used to calculate the optimal weights of the financial prediction. The mathematical models for the feed forward algorithm are as follows:

$$Input_j = y_j = \sum x_i w_{ij} \quad (2)$$

$$f(x) = \frac{1}{1+e^{-y_j}} \quad (3)$$

$$Error = T_k - O_k \quad (4)$$

Where, x_i is the input of preceding neurons, w_{ij} represents weights, $f(x)$ is a sigmoid that is used as the activation function for the hidden and output neurons, T_k is the observed (True) output while O_k is the calculated (actual) output. The algorithm works as follows:

1. Set all weights to random values ranging from -1.0 to +1.0
2. Set an input pattern (decimal values) to the neurons of the net's input layer
3. Activate each neuron of the following layer:
   (i) Multiply the weight values of the connections leading to this neuron with the output values of the preceding neurons
   (ii) Add up these values
   (iii) Pass the result to an activation function, which computes the output value of this neuron
4. Repeat this until the output layer is reached
5. Compare the calculated output pattern to the desired target pattern and compute an error value
6. Change all weights by adding the error value to the (old) weight values
7. Go to step 2
8. The algorithm ends, if it fulfills its criterion.

(b) Back Propagation Algorithm: Backpropagation is a supervised learning algorithm and is mainly used by Multilayer perceptron to change the weights connected to the network's hidden neuron layer(s). The backpropagation algorithm uses a computer output error to change the weight values in backward direction. To get this net error, a forward propagation phase must have been done before. While propagating in forward direction, the neurons are being activated using the sigmoid activation function. The formula of sigmoid activation is shown in equation (3). The backpropagation algorithm is used to adjust the new weights to be trained in the network. The following are the mathematical models for the backpropagation algorithm:

The error in the output layer is calculated by using the formula in equation (5).

$$\delta_k = O_k(1 - O_k)(T_k - O_k) \quad (5)$$

$$O_k = \frac{1}{1+e^{-y_k}} \quad (6)$$

Where, O_k is the calculated (actual) output expressed in equation (6), and T_k is the observed (True) output. The backpropagation error in the hidden layer is calculated by using the formula in equation (7).

$$\delta_j = o_j(1 - o_j) \sum_k \delta_k * w_{jk} \quad (7)$$

Where, w_{jk} is the weight of the connection from unit j to unit k in the next layer and δ_k is the error of unit k. The weight adjustment formula in equation (8) is used to adjust the weights to produce new weights after a successful epoch.

$$W_{new} = W_{old} + \eta * \Delta W \quad (8)$$

Where, η is a constant called the learning rate. The learning rate takes value between 0 and 1. ΔW is the change of weight after each instance of training dataset is passed through the network. The algorithm works as follows:

1. Perform the forward propagation phase for an input pattern and calculate the output error
2. Change all weight values of each weight matrix using the formula Weight (old) + learning rate * ΔW
3. Go to step 1
4. The algorithm ends, if it fulfills its criterion.

(c) Ensemble Model Combination: Model averaging is used as the combination technique, with each of the network models serving as the base models for the parent model. Model averaging is the easiest of the combination techniques which is simply averaging the outputs of the three networks to get an average predictive error. The number of neurons is the same for each network; the input layer has four neurons, the hidden layers are 3 for each network with 6, 5, and 3 neurons respectively. The number of layers and neurons were chosen heuristically. The number of neurons in the output layer is one as the modeling applied in the study aims to predict one step ahead closing value in the future forecasting.

$$Output\ overall = (Outputk_1 + Outputk_2 + Outputk_3 + \cdots Outputk_n)/n \quad (9)$$

Where, *n* is the total number of network models used in the ensemble model.

4. Results and Discussion

4.1. The Ensemble Model

The architectural design in Fig. 5 shows a modeling sample of three artificial neural network algorithms with high variance ‘ensembled’ to produce efficient forecasting model to unravel the market mysteries for accurate decision on investment. It was designed such that it trains multiple models by positioning them to learn in different ways. The average of the results of each of the Neural Network models with low bias and high variance, are computed to produce efficient output better than the output of a single model. This mechanism will minimize the inaccuracy in forecasting the stock price and achieves the vital idea of better stock market prediction results.

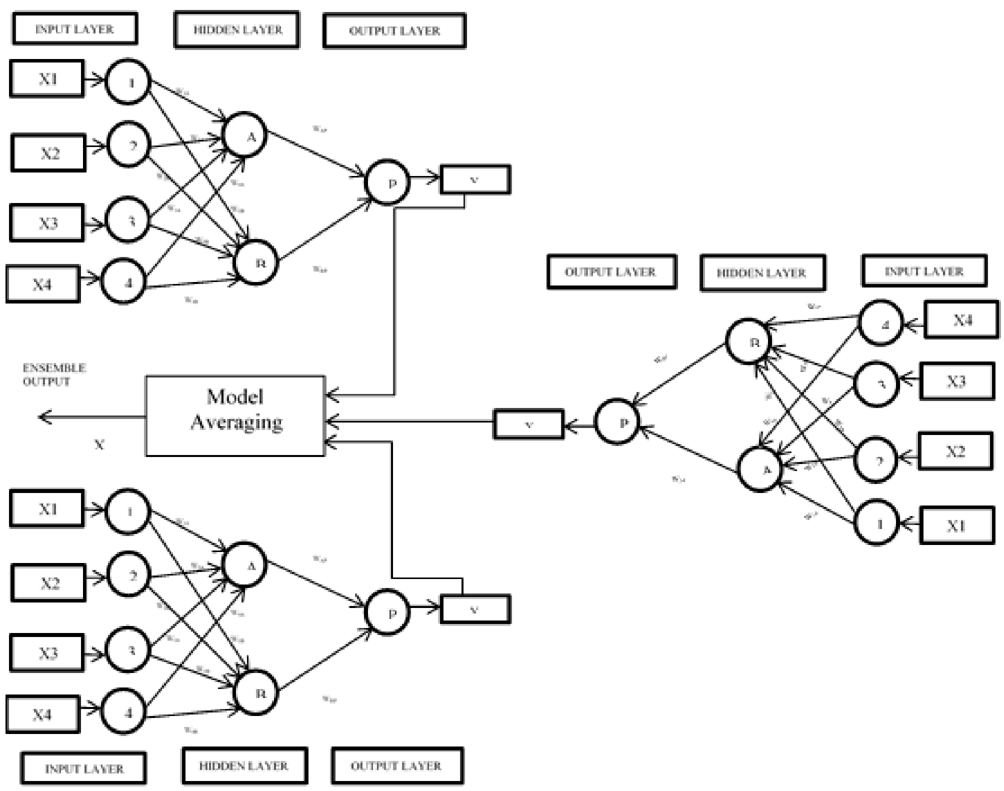

Fig. 5 Architecture of the Ensemble Model.

The components of the architectural design in Fig. 5 are as follows:

1. Stock Exchange Values: The stock exchange values are the historical data of the problem domain used for machine learning training and prediction.
2. Input layer: The input layer supplies the training dataset to the hidden layer nodes. The variables x_1, x_2, …, x_n holds the stock market values inputs data to be evaluated. These inputs are duplicated and sent to the hidden nodes.
3. Hidden layer: In the hidden layer ensemble learning mechanism uses intuitive method to address the problem of overfitting. During model learning overfitting occurs due to too much from the training data. It can be fixed by training multiple models, each of which will learn from the data in different ways. Such that each component model learns a relationship from the data that contains the true signal with some addition of noise, a combination of models should maintain the relationship of the signal within the data while averaging out the noise.
4. Output layer: After the multiple models have been combined from the results of the hidden layer, the outer layer combines the predictions from each of the multiple neural network trained models to reduce the variance of predictions and reduce generalization errors.
5. Model Averaging (Ensemble Strategy): Assembly of networks that have the same configuration and different initial random weights were trained on the same dataset. At the point of the convergence of the iteration minimal errors, each of the models is then used to make a prediction and the actual prediction is calculated as the average of the predictions.

4.2. Evaluation of the Models

Table 2 displays the performance of four trained networks and the ensemble model, on selected dates from the test dataset for Access Bank. Input parameters were previous four closing prices. The networks were trained using NeurophStudio, a Java GUI framework dedicated to training neural networks.

Table 2 Comparison of the Trained MLP Networks, the Ensemble Model and Actual Output.

Date	Actual	NN1	NN2	NN3	NN4	Ensemble
26/03/2020	6.15	5.96654	5.99741	5.97977	5.97473	5.979613
08/05/2020	6.4	6.42896	6.4151	6.43274	6.39998	6.419195
02/09/2020	6.4	6.40439	6.42077	6.41069	6.38675	6.40565
21/09/2020	6.4	6.40565	6.39683	6.41447	6.39872	6.403918
20/10/2020	7.75	7.74062	7.74881	7.76204	7.75385	7.75133
30/12/2020	8.75	8.71649	8.80532	8.77886	8.73728	8.759488
31/12/2020	8.45	8.54954	8.59553	8.61128	8.56214	8.579623

From the table, it can be seen that for any day or instance, the ensemble model must give at least an average prediction or at most, the closest prediction to the actual value. Table 3 displays the mean square error (MSE) of the four trained networks and ensemble model, on the randomly selected dates in Table 2. Also, Table 4 shows the rank in predictive accuracy to the actual stock value of the different networks and ensemble model.

Table 3 Displays the MSE for the Randomly Selected Dates.

Date	NN1(MSE) L.R: 0.2 M.R: NIL	NN2(MSE) L.R: 0.2 M.R: 0.7	NN3(MSE) L.R: 0.2 M.R: NIL	NN4(MSE) L.R: 0.2 M.R: 0.4	Ensemble(MSE)
26/03/2020	0.000853	0.00059	0.000734	0.000778	0.000736
08/05/2020	1.76E-05	4E-06	2.3E-05	1.6E-07	7.02E-06
02/09/2020	9E-08	8.41E-06	1.69E-06	6.25E-06	2.5E-07
21/09/2020	2.5E-07	8.1E-07	3.61E-06	3.6E-07	5.06E-08
20/10/2020	2.56E-06	9E-08	3.24E-06	2.5E-07	1E-08
30/12/2020	3.25E-05	7.06E-05	1.76E-05	5.76E-06	1.27E-06
31/12/2020	0.00025	0.000534	0.000655	0.000317	0.000423

$$MSE = mean(a_i - p_i)^2 \quad (10)$$

Where, a is the actual value, and p is the predicted value.

Table 4 Rank in Predictive Errors of the Randomly Selected Test Dates and Ensemble Model.

Date	NN1(MSE)	NN2(MSE)	NN3(MSE)	NN4(MSE)	Ensemble(MSE)
26/03/2020	5	1	2	4	3
08/05/2020	4	2	5	1	3
02/09/2020	1	5	3	4	2
21/09/2020	2	4	5	3	1
20/10/2020	4	2	5	3	1
30/12/2020	4	5	3	2	1
31/12/2020	1	4	5	2	3
Average	3	3.29	4	2.71	2

From the rank, we can see that for any day or instance, the ensemble model must give at least an average predictive error and at most, the best predictive error. The trained networks perform poorly at different instances. The graphical representations of actual and predicted prices of the companies are shown in Figs. 6 – 12. The horizontal axis in the graphs denotes randomly selected dates for forecasting and the vertical axis denotes the respective stock price for Access Bank.

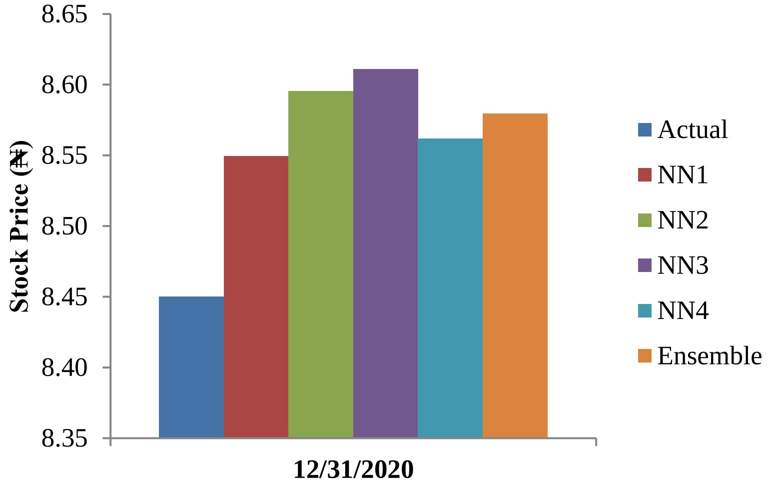

Fig. 6 Performance of the base networks and ensemble model for 31/12/2020.

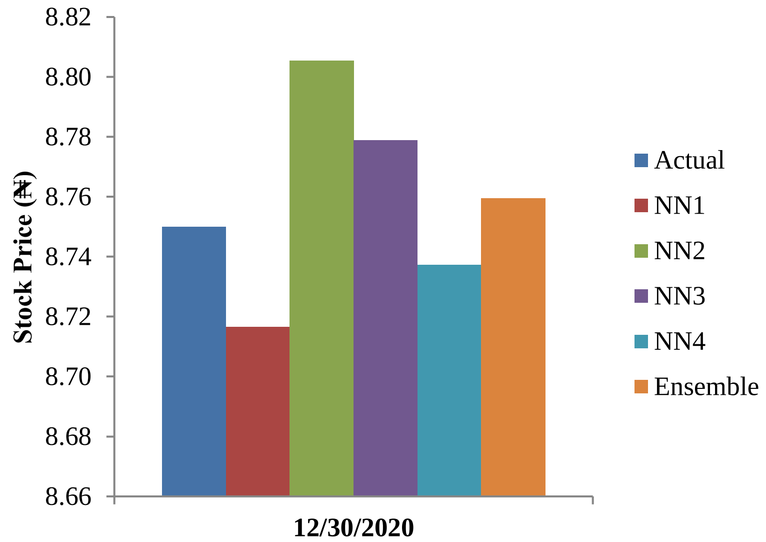

Fig. 7 Performance of the base networks and ensemble model for 30/12/2020.

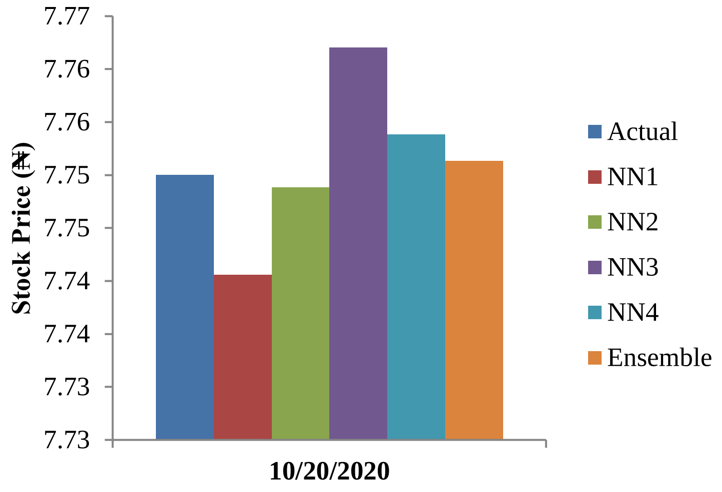

Fig. 8 Performance of the base networks and ensemble model for 20/10/2020.

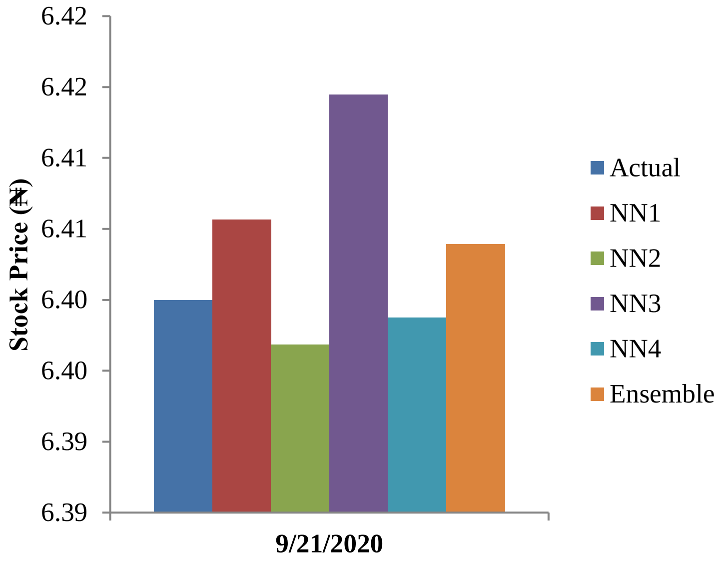

Fig. 9 Performance of the base networks and ensemble model for 21/09/2020.

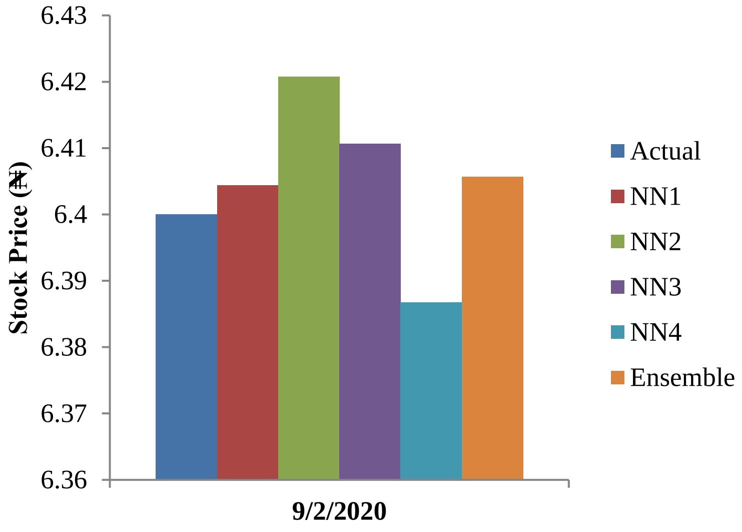

Fig. 10 Performance of the base networks and ensemble model for 02/09/2020.

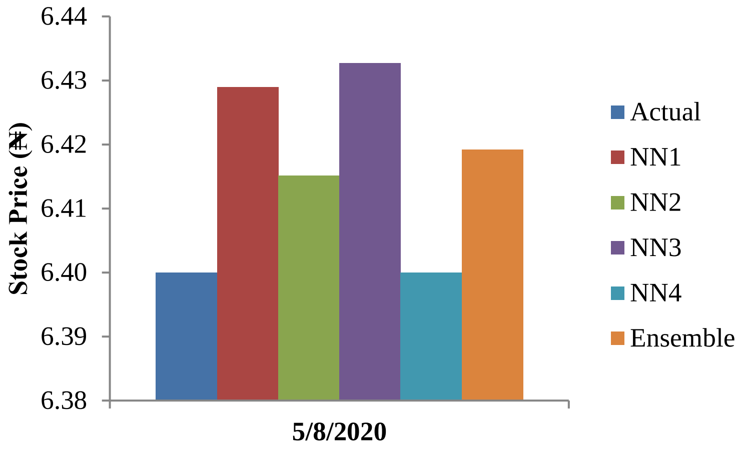

Fig. 11 Performance of the base networks and ensemble model for 08/05/2020

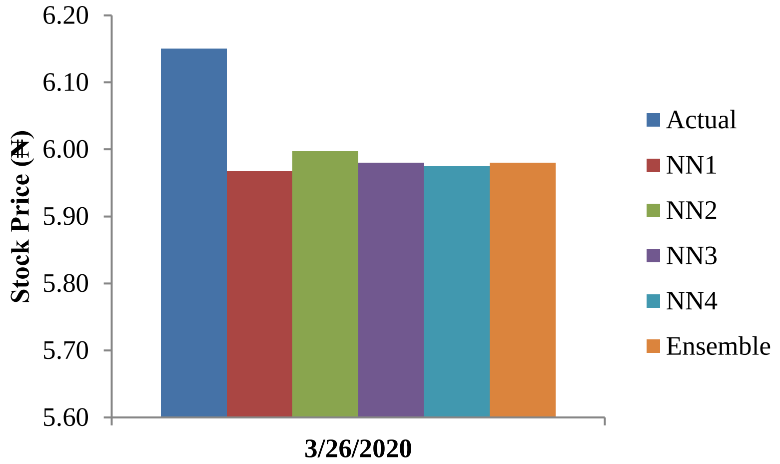

Fig. 12 Performance of the base networks and ensemble model for 26/05/2020.

4.3. Summary of Results

This work proposed an efficient forecasting model using Ensemble Artificial Neural Network to unravel the market mysteries for accurate decision on investment. The ensemble forecasting models integrated multilayer perceptron architecture based on Back Propagation Algorithm to predict the stock market performance. The proposed mechanism trained multiple models by positioning them to learn in different ways. The model creates a set of neural network models with low bias and high variance, and proceeds to compute the average of the results of each of the Neural Network models. The outcome of the proposed mechanism had shown average to minimum error forecasting of stock price and it achieved the vital idea to successful stock market prediction results as shown in the Table 3.

The implementation of the proposed model was designed on the theory of ensemble averaging which depends on two artificial neural network properties. The first approach of it was done such that the bias may be condensed on the account of an increased variance in any network. And in a cluster of networks, the variance can be condensed at a little trade off from the bias. Therefore, the results of the proposed mechanism gave better network with low bias and low variance generated from the combination of a group of networks each with low bias and high variance created at the initial computational stage of the proposed model. The processes are recursive such that the errors are backpropagated through the nodes, the connection weights are changed. During the process of backpropagation of errors through the network when different input patterns are presented to the network, the error is gradually reduced to a minimum. Training continues until the errors in the weights are sufficiently small to be accepted.

The predictions of the proposed model will guide the stock market experts for decision making on appropriate trend for investment. From Tables 2 – 3, and Fig. 6 through Fig. 12, prediction of the proposed Ensemble Neural Network model was compared with traditional Multilayer Perceptron Neural Network algorithms. It shows that the proposed Ensemble model is a better predictive model then the traditional Multilayer Perceptron algorithms with average to minimum error of prediction.

5. Conclusion

Forecasting stock indices is very difficult because of the market volatility from factors such as Political influence, macro-economic indicators, movement of other stock market prices, human psychology. Determining effective ways of stock market index prediction is important for stock market investor to aid investment decisions. This study has successfully developed an effective forecasting model using Ensemble Artificial Neural Network to unravel the market mysteries to enable decision making on stock market investment. This study 'ensembled' multiple neural network multilayer perceptron architecture models, which were based on backpropagation learning algorithm to predict the stock market performance. The prediction error of the proposed model was tested using real world stock market values. From 'Table 2', it is seen that the output of the ensemble model outperformed the traditional neural network multilayer perceptron models. At worse, the ensemble model gave an average predictive error as seen in 'Table 3', as compared to the predictive error of the other traditional neural networks. From this study, it is recommended that the model be adopted to guide stock market investors on stock market investment, as it would provide efficient solution for the highly fluctuating (rise and fall) indices of stock market outcome that affects the investor's belief. And it has the potentials to minimize the inaccuracy in forecasting the stock price and gives a reliable guide or vital ideas to successful stock market prediction results. For further work, research on involving macroeconomic factors as input variables can be made.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

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